Which Ladder to Climb? Evidence on wages of workers, jobs, and plants*

Christian Bayer† Moritz Kuhn‡

October 27, 2016

Abstract

How much does your wage depend on for whom you work relative to what job you do? To answer this question, we use linked employer-employee data from a representative German administrative survey which provides exceptionally detailed information on job characteristics, earnings, and hours. In this data, observables can explain more than 80 percent of wage variation. This allows us to decompose wages into an individual, a plant, and a job component. Among the three, the job component, most importantly the hierarchy level of a worker, explains 40% of the rise in average wages and almost all the rise in wage inequality over the life-cycle. The plant component, i.e. transitions from low-paying to high-paying plants, by contrast account for only 20 % of the life-cycle wage increase.

Keywords: income inequality, job shopping, sorting, careers

JEL-Codes:

*We thank Iourii Manovskii and participants at the REDg meeting 2016 for helpful comments and remarks.

†Universität Bonn and CEPR, Adenauerallee 24-42, 53113 Bonn, Germany, *email:* christian.bayer@uni-bonn.de

‡Universität Bonn, CEPR, and IZA, Adenauerallee 24-42, 53113 Bonn, Germany, *email:* mokuhn@uni-bonn.de

1 Introduction

How important is it for whom you work relative to what job you have? How important are your individual characteristics for your wage? These questions are at the core for our understanding of the labor market. We use the detailed information on worker and job characteristics to decompose wages in three (largely) orthogonal parts. First, an *individual component* that is attached to the individual and will neither change by changing job nor employer (e.g. education and age). Second, a *plant component* that will only change when the employer changes (labor market mobility). Third, a *job component* that can change over the career of a worker even within a plant (e.g. occupation, hierarchy level). We then use this data to examine the importance of career progression, labor market mobility, and experience to explain the increase in income over a worker's working life as well as the rise in income inequality over working life.

We find that all components together can explain over 80% of the observed cross sectional variation in wages. This large explanatory power of observables is outstanding compared to most existing studies that typically can explain only about one third of cross-sectional wage variation. At the same time, it is this high degree of statistical determination that allows us to decompose wages into an individual, a plant, and a job component without having a dominating unexplained component.[1]

Key for the high degree of statistical determination is that our data provides detailed information on jobs. The *job component* alone explains 40% of the life cycle increase in average wages and almost all the life-cycle increase in wage inequality. The *plant component*, i.e. difference between low-paying to high-paying plants and mobility across those, explains another 20% of the life-cycle increase in average wages but virtually none of the life-cycle increase in inequality. This seems to contrast to other studies that have recently highlighted the importance of firms in explaining the *secular* increase in inequality [see e.g. Song et al., 2015]. However, we also show that when job characteristics are ignored, plants appear to be more important both in explaining average wage increases as well as the life-cycle profile of inequality. In other words, high-paying plants are high-paying because of their job composition rather than some other intrinsic characteristics of the plant. Hence, the average human capital in the plant determines its average wage level. On top comes the utilization of the human capital, even fundamentally high-paying plants have a larger fraction of jobs in higher levels of hierarchy, better paying occupations, or other characteristics that more

[1] Although this is a high explanatory power, it is not exceptional and is also found for other administrative linked employer-employee data (see for example Strub et al. [2008]).

intensely utilize the human capital of an employee.

Our data base is the German *Survey of Earnings Structure* (SES), a large administrative sample that offers linked employer-employee microdata representative for the universe of German employees and employers, working at plants with at least 10 employees. It has roughly 3.2 million employee observation (roughly 10% of all employment). An important feature of the data is that it is directly obtained from human resource departments of plants and includes actual (virtually uncensored) paycheck information, hours worked, detailed descriptions of a workers education, occupation, age, tenure, and importantly an employee's level of hierarchy. Measurement error on all characteristics can therefore be expected to be particularly low.

The key information that our data contains about the job of an employee that is unavailable or unreliable in many other data sources is information about an employee's level of hierarchy (or responsibilities) –in some sense the effective level of human capital the employee *utilizes* on her current job. In fact, within the job component it is this variable, effectively capturing careers, which explains the dominant fraction of average income growth over the life cycle. Similarly, career paths are key to explain the evolution of inequality in the cross-section and that different career profiles explain virtually all the increase in income inequality over the life-cycle.

Importantly, taking into account hierarchy information changes what we know about the importance of both plants and education in explaining the evolution of inequality over the life-cycle. Without taking hierarchy information into account, education, i.e., human capital *capacity*, explains much of the increase in inequality over the life-cycle and also the dispersion of plant components in incomes increase with age.

When we take hierarchy information into account, there are little differences in returns to experience by different educational groups, and in stark contrast to what explains the increase in inequality over *time* (Song et al. [2015]), mobility and differences between plants seems to contribute not much to the increase in income inequality over *working life*. The contribution to cross-sectional wage inequality is flat over working life and accounts for roughly 30 %.

We view these facts as informative about the labor market structure and the importance of job search and sorting for earnings dynamics. Importantly, we find that the career ladder is the dominating force for earnings dynamics over the life-cycle. The importance of the career ladder does not mean that mobility and for whom a worker works is not important. It is important that workers have the opportunity of a career at the employer and some employers might not offer these career prospects.

The fact that much of income differences can be explained by a observable *job component* suggests that much of the productivity of an employer-employee match is job-specific not match-specific, i.e. when a highly productive match is destroyed and the job is refilled with another worker the productivity remains high. Still, the match requires to be productive a person with the right amount of human capital to be utilized. Hierarchies likely reflect (optimally) chosen structures of production that need to be taken into account when trying to model earnings dynamics and the resulting inequality as an outcome of labor market search.

Motivated by these findings, we collect and digitalize archived data from historical waves of the SES and the *Quarterly Survey of Earnings* (QSE) (Vierteljährliche Verdiensterhebung). The data is not available at the employee level, but still fairly disaggregated in age-industry-hierarchy, age-occupation-hierarchy, and age-plant size-hierarchy cells for the SES and industry-hierarchy cells for the QSE. In addition, both data sources provide separate information for males and females. We find that the characteristics that are available in the QSE account for 2/3 of the earnings variation in the 2001 SES. To decompose the changes in aggregate wage inequality in changes in the distribution of employees across job and plant characteristics and in changes of returns to job and plant characteristics. We find ...

[TO BE DONE]

The remainder of the paper is organized as follows: Section 2 introduces the data set our analysis is based on. Section 3 reports results on the decomposition of wage growth and rising wage inequality. Section 4 provides a robustness and sensitivity analysis. Section 5 provides some evidence on time trends. Section 6 concludes.

2 Data

We use data from the 2006 Structure of Earnings Survey ("Verdienststrukturerhebung"), henceforth SES, for most of our analysis. The SES data is an administrative representative survey of establishments (short: plants). The survey is conducted by the German Statistical Office and establishments are legally obliged to participate in the survey so that selection due to non-response does not arise. The data is linked employer-employee data so that it contains establishment-level and employee-level information. Establishments with 10 to 49 employees have to report data on all employees. Establishments with 50 and more employees

report data only for a random subgroup of employees. Small establishments with less than 10 employees are not covered by the data. The data also contains information about the employment share of the establishment in total employment of the firm. We will exploit this information to study also single plant firms in a sensitivity analysis. Data on regular earnings, overtime pay, bonuses, hours worked, both regular and overtime, are extracted from the payroll accounting and person master data of establishments and directly transmitted via software interface to the statistic office. Transmission error is therefore negligible.
The data covers public and private employers in the manufacturing and service sector. Self employed are not covered. In total, the data has information on roughly 28,700 establishments with about 3.2 mio employees. The data is representative for 21 mio workers in Germany.
We focus on male workers age 25 to 55 in West Germany and drop a few censored earnings observations (29 observations).[2] We drop further all observations for which the state has a major influence (75,016 observations).[3] Our wage measure is monthly gross earnings including overtime pay and bonuses divided by regular paid hours and overtime hours. We trim the sample by running a regression on a set of dummy variables and firm fixed effects and then censor the left and right 0.01 % of residual earnings from a regression of log wages on these variables from our sample (208 observations). The variables in the regression include all variables that we use below in our analysis. We provide details on the regression in Appendix B. We also drop all observations for which only a single worker at the plant is left after our sample selection (51,361 observations). In total, we have 1,043,295 observations in our sample.
The data is exceptional as it can explain more than 81 % of wage variation in the cross-section if we use plant fixed effects. Even without plant fixed effects but with firm-level controls 69 % of wage variation in the cross-section can be explained. This allows us to study the determinants of wage variation to an extend that is unheard before. Part of this high explanatory power is due to the high quality of the data. A second part is as we will show below due to the information about workers' job and hierarchy level.
The data distinguishes five levels of hierarchy. These hierarchy levels are defined based on the skill requirements, typical educational requirements, task complexity, and decision mak-

[2]The censoring limit is at 1 mio Euro annual gross earnings.

[3]For a large set of observations this information is missing. The information is only available if in a region-industry cell there are at least 3 firms in which the state has a major influence. Major influence is defined as owning 50 percent of stocks or due to other regulation.

ing power.[4] The lowest level are workers who perform simple tasks (*untrained workers*). The tasks for these workers typically do not require particular occupational training (apprenticeship) and can be learned on the job in less than 3 months. The second level, (*trained workers*), is working on tasks which require some occupational experience but no full occupational training (apprenticeship). Tasks performed on this hierarchy level can be typically learned on the job in less than 2 years. Both lowest groups do not undertake independent decisions. The third level are workers who for their tasks need particular occupational training (apprenticeship) and in addition occupational experience (*assistants*). Preparing decisions or actually making them in a well defined and narrow area is typically part of the workers task (an example would be a tradesman, a junior clerk, or a salesman). The fourth group are workers on tasks that require either specialized (academic) training or occupational training (apprenticeship) and experience (*professionals*). Importantly, they perform their tasks independently and have some decision-making power that regards others. Typically these workers oversee small teams (an example would be a foreman). The fifth hierarchy level is managers and supervisors (*management*) in the sense that their primary task is to do strategic and independent decision-making. The managers constitute the highest hierarchy level but typically they are not reported separately so that we have one management group at the top of the hierarchy with managers and supervisors. We provide further details in appendix A. Importantly, the hierarchy variable captures a functional concept within an establishment not a qualification concept. Hence, hierarchy, while correlated with formal education are job (i.e. task) specific and can be best thought of as capturing the *utilization* of human capital, while education captures past human capital investments. In fact, Table 1 shows that a substantial fraction of workers is employed in all hierarchy levels for virtually any level of formal education (with the exception maybe of extreme combinations) and that workers progress along the hierarchy dimension as they get older, which both clearly indicates that formal education and the hierarchy variable measure two distinct concepts. Similarly, hierarchies and (3-digit) occupations measure two different concepts (think of the occupation "chef" within which hierarchies would capture the difference between dishwashers, kitchen assistants, commis, chefs de partie, and sous- and head-chefs).[5]

Insofar, the hierarchy levels have similarities to 4 or more digit codes for occupational classification like the ISCO 08 or KldB 2010 for Germany. The major occupational codes of ISCO contain information about the skill requirement of workers. The German equivalent,

[4]We discuss below similarities to modern occupational codes.

[5]In theory 4/5 digit occupations regularly capture hierarchy levels. In many survey data sets, e.g. the CPS, these measures seem to be plagued with measurement error, see e.g. **?**.

Table 1: Share of hierarchy levels within formal education and age groups

	at age 25 - 35					at age 35 - 45				
	untrained	trained	assistant	professional	management	untrained	trained	assistant	professional	management
Secondary education	22.89	40.85	26.69	8.28	1.3	15.52	39.25	31.63	11.55	2.04
Vocational education	5.06	16.43	59.3	16.97	2.24	3.05	12.72	51.56	26.13	6.54
University degree	8.02	17.4	29.24	27.8	17.55	4.67	12.2	21.74	31.76	29.64

Notes: Relative frequencies in percentage points within age groups. Shares sum across columns within age groups to 100. Secondary education contains all workers with secondary education but no vocational training. Vocational education are workers with secondary education and in addition a vocational degree. University degree are all workers with university or technical college degree.

KldB 2010, used by the German employment office for labor market statistics encodes the skill requirement in the last digit of its 5-digit version.
Still, the functional hierarchy information is conceptually distinct from the occupational information. Occupational information allows for a horizontal distinction regarding the tasks and duties in a job. The hierarchy information like the skill and specialization requirements in ISCO codes allow for a vertical distinction within group of workers who perform certain tasks and duties. Managers have different tasks and duties and are also typically not horizontally differentiated in the ISCO codes.

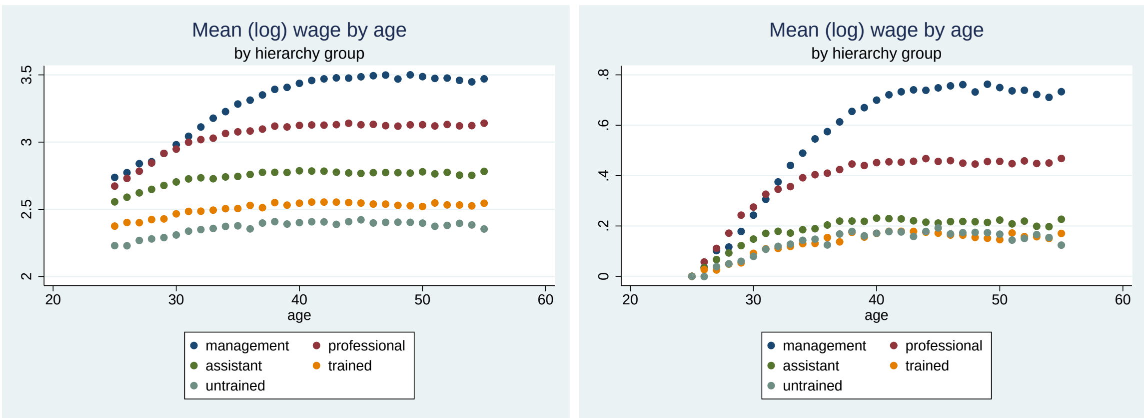
3 Results

First, we analyze the main factors driving average wage growth over the life-cycle. Thereafter, we discuss what drives the rise in wage inequality over the life-cycle.

3.1 Average wages over the life-cycle

Over the life-cycle, the average wage of an employee increases substantially. In our data, the average wage of a male worker increases by roughly 2.5% with every year of age between age 25 and age 45 and levels off afterwards (45 log points between age 25 and age 45 see Figure 2). Yet, this average wage increase masks substantial heterogeneity. Figure 1 reports the mean log wage difference to age 25 by age conditioning in addition on worker's hierarchy level. We find that the top hierarchy group has always the highest wage and sees the strongest increase in wages with age so that the wage differences to the other groups widen with age. For example, a worker constantly remaining at the *assistant* hierarchy level will have a 0.2 log point (22%) increase in his wage over his life, while at the management level, wages rise by 0.8 log points (123%). A worker climbing up the career ladder from untrained worker to management, will see a stellar 1.2 log point (232%) increase of his wage over his life.

Figure 1: Wage by age and hierarchy level



(a) Mean level (b) Growth

Notes: The left panel shows mean (log) wages by age for different hierarchy levels. The right panel shows the change in wages with age for the different age profiles. This is done by normalizing age profiles from the left panel to zero at age 25.

This suggests that moving up the hierarchy ladder might be an important contribution to life-cycle income growth. Other potential contributions to income growth could be effects of occupational mobility, mobility towards better paying firms, further formal education (or an increase of the share of more educated workers by age), or pure returns to experience. To decompose the wage increase over the life-cycle, we run a cross-sectional regression of log wages on dummy variables. We collect variables in three groups that we label *plant*, *individual*, and *job* component. In addition, there is a pure experience component that is residual and measures the average income growth with age that cannot be explained by workers of different age showing different, individual, job, or firm characteristics.

The *individual component* comprises worker characteristics that are not driven by labor market events. In our case this is only education. The *plant component* comprises plant characteristics that change with labor market mobility. In out case, we measure this by estimating a plant fixed effect. As a robustness, we run an alternative where we only use observable plant characteristics (employment size, industry, region, and the presence of a collective bargaining agreement). Finally, the *job component* captures characteristics that can change while staying with an employer but changing jobs. In our case, these are hierarchy level, the type of employment contract (fixed-term contract, apprenticeship, permanent, etc.), a part-time/full-time flag, and the occupation.

Figure 2 reports the decomposition of mean log wages into these components. For this purpose, we regress the log wage on worker (excluding age), job characteristics, and plant fixed effect, then we calculate the wage growth contribution of a component by calculating the implied wage growth over the life-cycle due to changes in observable characteristics.

Overall, changes in observables can explain 60 - 70 % of wage growth by age. Job components alone explain almost 40 %, while labor market mobility (plant component) only accounts for 20 % wage growth. The worker component is negligible. We conclude from this evidence that most of life-time wage growth results from worker's careers over jobs. We discuss the relation between tenure with the same employer and stages on the career ladder below.

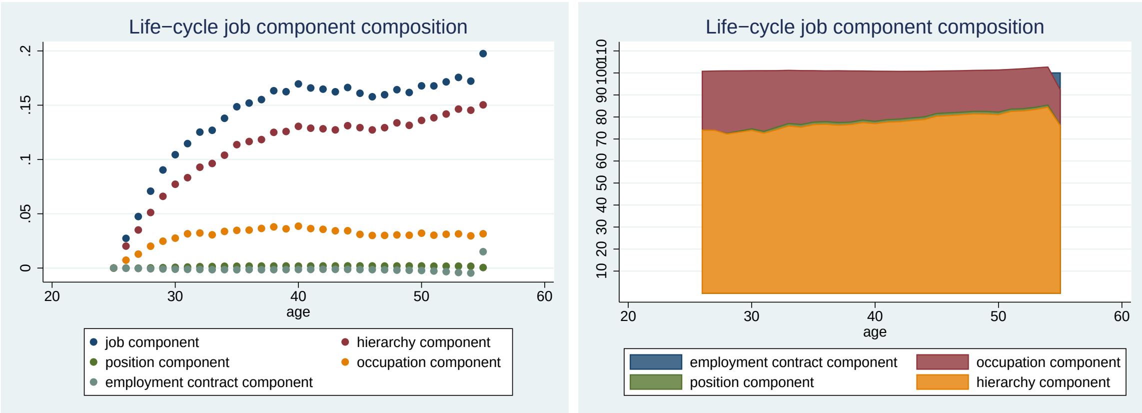
Figure 2: Wage Growth Compared to age 25

(a) Growth by component

(b) Contribution to growth

Within the job component, the promotions along the hierarchy dimension are key to explain average wage growth, as Figure 3 shows. For this figure, we break up the job component into its subcomponents. Promotions explain 70 - 80 % of the wage growth within the job component, or conversely roughly 50 % of all wage growth. (3-digit) Occupational mobility accounts for 15 to 25 percent of the job component. Position (full-time vs part-time) accounts for only a small fraction of wage growth.

Figure 3: Subcomponents of job component by age



(a) Component level (b) Component share

Notes: The left panel shows normalized sub-components (hierarchy, position, employment contract, occupation) of the job component by age. The right panel shows the relative shares. The shares add up to 100 percent of the job component by construction.

3.2 The life-cycle of wage inequality

The overall explanatory power of the observables of a regression of log hourly wages in our data is large. The overall R2 is 0.81. A degree of explanatory power that is typically unheard of in this type of regression. Hence, the data comprises a large set of characteristics that are linked to cross-sectional wage differences. It is important to note however that this is not due to a small overall wage variation. The Gini coefficient of annual gross earnings is 0.30; in the 2007 SCF, the corresponding Gini coefficient is 0.43.

As observables explain most of the wage growth over the life-cycle, we next explore how well observables can explain the inequality within an age group. Figure 4 shows the variance of log wages by age. We find the typical pattern of an almost linear increase of the cross-sectional variance. The increase of the variance is substantial with 0.12 log points over 30 years or 0.004 per year. **?** find a comparable number for household incomes taken from SOEP data. Heathcote et al. [2010] report for the U.S. depending on the data source an increase between 0.17 and 0.20 log points over the same part of working life.

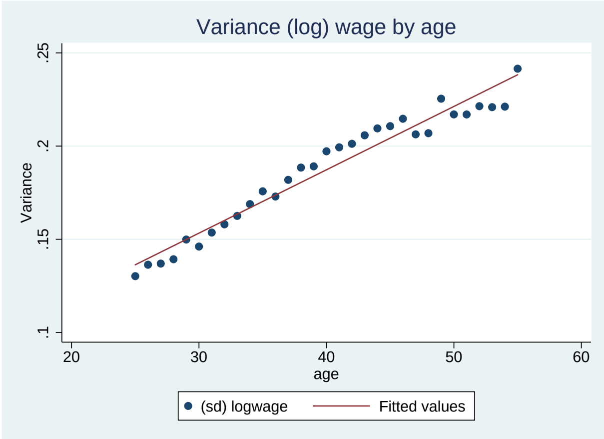


Figure 4: Variance of log wages by age

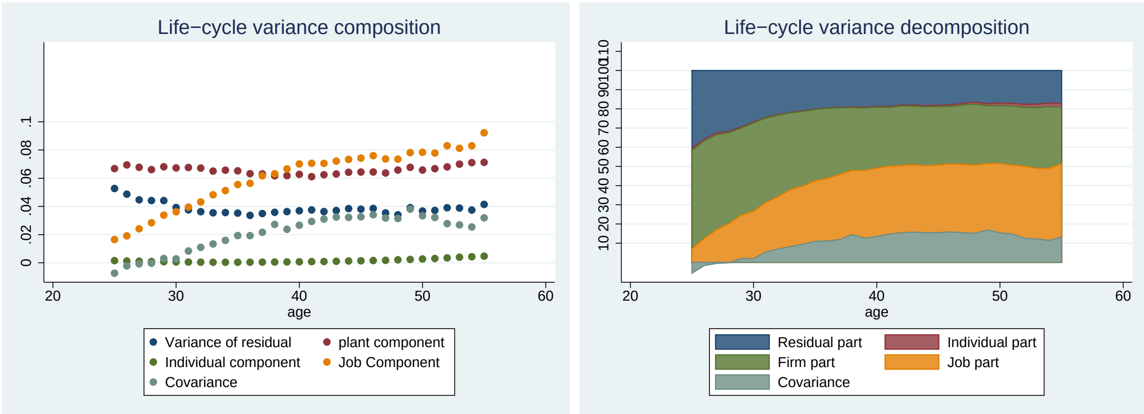
Conditional on age, observables explain between 2/3 and 4/5 of the cross-sectional wage dispersion, see Figure 5 (b). Differences in average wages between plants are the most important source of inequality among young workers explaining roughly 50% of their wage inequality. Strikingly, however, and despite the importance of moves to better paying firms for average wage growth, the age profile of the plant component is entirely flat. Workers, while on average sorting into better paying firms over their life-time, these sorting dynamics seem not to lead to wage compression over time.

The other, and maybe even more striking fact, see Figure 5 (a) is that the job component explains *entirely* the increase in wage inequality over the life cycle. This result is robust to looking at alternative measures of inequality, such as the interquartile range or the P10/P50 and P50/P90 ratios, see Appendix.

Within the job component, it is again hierarchy that explains most of the increase in inequality. In words, our data tells us that it is the careers of workers, i.e. being assigned to and/or factually qualified for different jobs, that create wage inequality. Note, that there is also a covariance component that arises with age and that accounts for 10 % at age 45.

Figure 6 decomposes the covariance component by splitting the covariance in components due to covariances between job, individual, and plant component by age. We find that the covariance between worker (education) and job component, while small overall, increases almost linearly with age. We interpret the finding as evidence for an increasing human capital utilization of firms along the career path.

Figure 5: Variance decomposition



(a) Component level

(b) Component share

Notes: Share of the variance of log wages by age accounted for by the job, individual, and firm component. We use firm-level controls to construct the firm component.

3.3 The (un)importance of plants

How does this square with the evidence that firms are important for and responsible for the increase in wage inequality over the past 30 years in the U.S? Table 2 gives a hint. It shows that both hierarchies and plants (most firms behind our plants are single plant firms) are important variables in explaining wage inequality. Yet, the very fact that the R^2 of the regression does that combines both is smaller than the sum of the R^2 statistics suggests and important correlation between plants and hierarchies. (Another striking observation is that 5 dummies for hierarchy levels explain over 40% of wage inequality.)

Better paying plants offer on average more jobs at higher levels of hierarchy, only low paying plants offer a substantial fraction of jobs on the lowest two hierarchy levels, see Table 3. Note that by using the plant effects from a regression that includes hierarchy levels, we sort plants according to whether they pay better *at all levels* of hierarchy, i.e. plant effects are not driven by having a larger share of top-level workers.

In fact, analyzing wage growth over the life-cycle ignoring the different employment shares of workers at different levels of hierarchy, leads to a substantial overestimation of the role of mobility between plants, as Figure 7 shows. In comparison to Figure 2, we overestimate the contribution of the plant component to wage by 70 to 150 percent (see figure 8).[6]

[6]Interestingly, also the residuals from this regression are no longer orthogonal to the plant component within age groups - while they are when including hierarchy. Well paying plants pay young workers worse than their old workers. The young worker of a well-paying plant is at a lower hierarchy level than the average

Table 2: Importance of Characteristics in Explaining Hourly Wages

	Plant Effects Only	Hierarchy Effects Only	Hierarchy and Plant Effects	Hierarchy, Plant, Occupation, and Education
(adj.) R^2	0.573	0.417	0.766	0.786

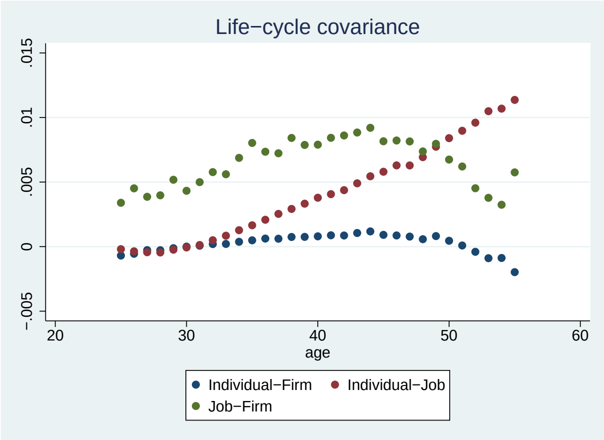
Notes: Adjusted R^2 of different regressions on log wages. First column regression only on plant fixed effects, second column only on hierarchy dummies, third column on hierarchy dummies and plant fixed effects, fourth column on hierarchy dummies, plant fixed effects, occupation dummies, and education dummies.

Table 3: Shares of employees by hierarchy level and tercile of the plant distribution

	management	professional	assistant	trained	untrained	Avg. No Empl.
top tercile	11.5	29.3	41.9	13.2	4.1	2,141
medium tercile	8.9	21.5	46.2	17.7	5.8	471
lowest tercile	15.3	17.0	38.4	21.1	8.3	6,854

Notes: Plants are ranked by their plant effect in the wage regression and sorted into terciles using plant weights. Hierarchy shares within plant tercile are given in percentage points and sum to 100 for each tercile. Observations are weighted by worker weights. Average number of employees is computed using worker weights.

Figure 6: Covariance of worker, job, and plant component by age



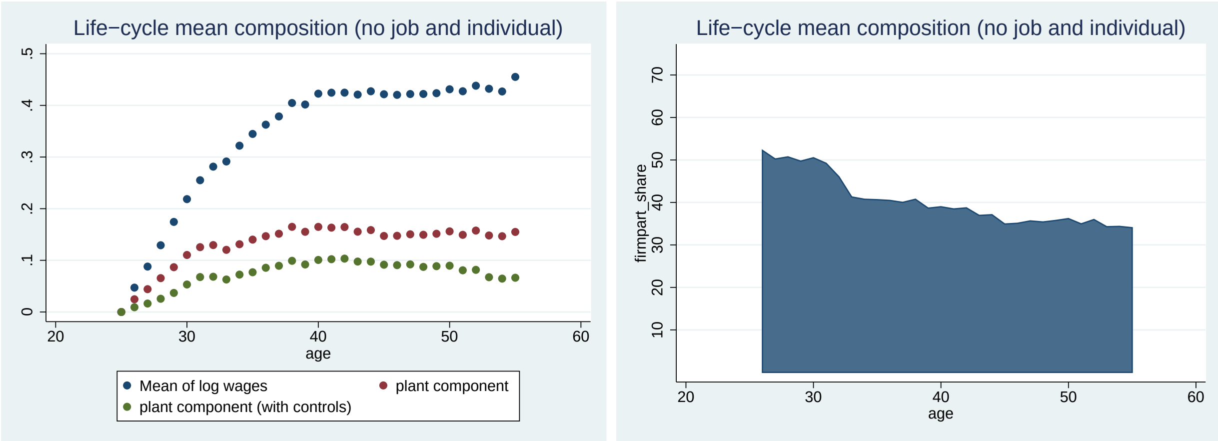
3.4 What makes a career?

Given the importance of careers, we next will try to shed some light on the question of what makes a career. As we have seen from Table 1, employees at higher levels of hierarchy are both typically older and better educated. One interesting question with important implications on worker reallocation is whether labor market mobility is enhancing or hindering career progress. Are careers best described by up-or-out principles or by job shopping across plants? To examine this question, we construct a measure of potential tenure. Potential tenure is age minus 16 for workers with occupational training and in case of workers with academic training, age minus 24. This means, that apprentices if they stay with their employer will have continuous tenure starting from age 16 although the first years might still be part of their education in the German dual education system. We observe actual tenure with the employer in the data. We then divide actual tenure by potential tenure as a measure of how much of his career a worker has spent with his current employer. To control for age effects, we consider only workers age 40 to 45 years.

We find that the share a worker has spent with his employer is increasing along the hierarchy ladder. At the bottom, the share is 23 % and at the top it is 45 %. Hence, people up in the hierarchy have spent almost half of their career with their current employer. We find that the career share with the current employer is steeply increasing with hierarchy levels and the highest three hierarchy levels all show career shares with the current employer between 43 % and 47 %. The cross-sectional average for all workers is 42 %. We conclude from this evidence that workers at the top of the hierarchy are not more mobile across employers than at lower

worker at that plant.

Figure 7: Decomposition of mean wage by age



(a) Component level (b) Component share

Notes: Decomposition of mean log wages using only firm fixed-effects but no individual or job characteristics.

levels. Labor market mobility for career progression seems therefore less important, nor does the data suggest much of an up or out principle. Labor market mobility is concentrated at low hierarchy levels but mostly the same for all trained and untrained workers at the two lowest levels of hierarchy.

Figure 9 shows the average career share by age for different hierarchy levels. We see that the highest hierarchy level spent most time of their potential career at their current employer.

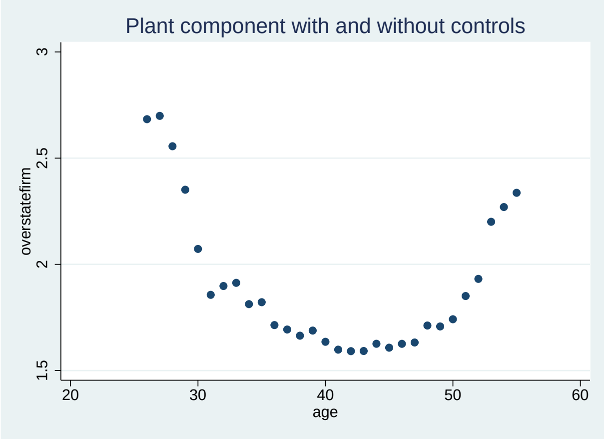
3.5 Pseudo panel 2006 - 2010

The data does not have a panel dimension so that we can follow individual workers over time. We use the repeated cross-section and information on worker characteristics to build a pseudo panel for the period from 2006 to 2010. We construct age workers where we exploit that for example a 40-year-old worker in 2006 will be 44 years old in 2010. We compute the cross-sectional across hierarchy levels by age in 2006 and 2010 and compare how this distribution changes as workers age. Figure **??** shows the distribution across hierarchy levels by age in 2006.

4 Robustness and Sensitivity

[TO BE DONE]

Figure 8: Increase of plant component without additional controls



Notes: Ratio of plant component without additional job and individual controls to plant component with controls (see figure 2).

Figure 9: Career share by age and hierarchy level

5 Trends in inequality

The Survey of Earnings Statistics has been carried out roughly every six years since 1951.[7] Micro data is not available for any year before 1990, but very detailed cross tabulations of average wages according to hierarchy and industry (plus regions and employee age in some years) are available for the older waves in print. In addition, the Quarterly Survey of Earnings (QSE) provides information at quarterly frequency since 1957 for average salaries at the various hierarchy levels, industries, and regions. Here, however, the top management is excluded from the surveys. We digitalized these data from printed publications and archived records. We use the newly created data set to reconstruct and decompose the evolution of monthly labor income inequality in Germany over the past 60 years. The hierarchical information until 2001 is more detailed than the five hierarchy groups available in the 2006 and 2010 surveys. In the earlier waves, there are three levels for blue collar workers and five waves of clerical and technical white collar employees ("technische Angestellte" and "kaufmännische Angestellte" respectively).[8] At the same time the older survey waves only cover the private business sector (roughly sectors B-K of the employment statistics).

[7]The survey was carried out in 1951, 1957, 1962, 1966, 1972, 1978, 1990, 1992 (only East Germany), 1995, 2000, 2006, and 2010.

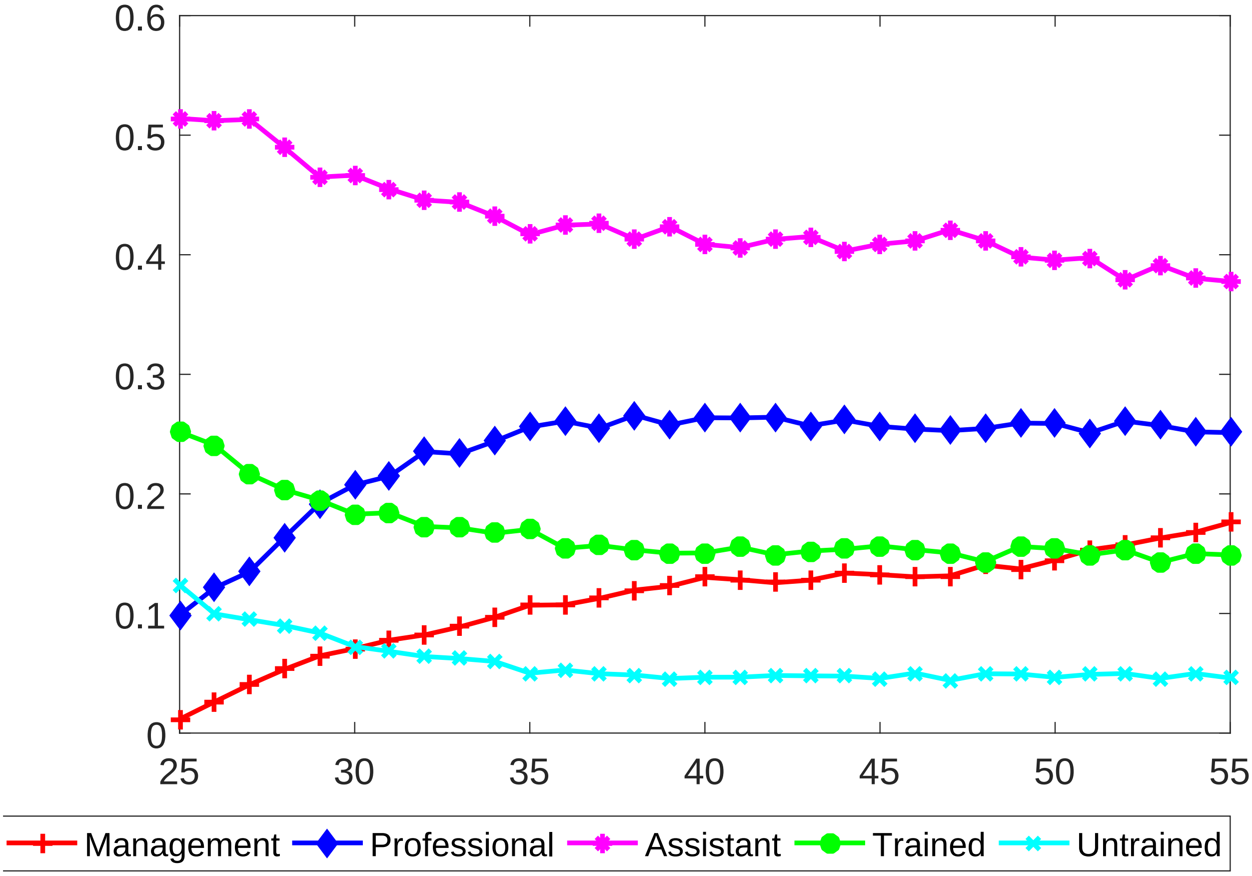
[8]The three blue collar hierarchies map into the three lowest hierarchy levels in the 2006/10 surveys, the lowest white collar level maps into the lowest level and the next three reported levels (the very highest is suppressed in the statistics) map into the top three levels of the newer surveys.

Table 4: Fraction of labor-market years spent with current employer by hierarchy group

	Management	Professional	Assistant	Trained	Untrained
Fraction of time at current employer	45%	47%	43%	32%	23%

Our first finding from this data is that both the structure of the labor force and the relative salary structures have (non-surprisingly) changed substantially over time. Figure 10 plots the share of blue collar, technical and clerical white-collar workers. Figure 11 plots the shares of the three main hierarchy classes within the blue and white collar groups.[9]
Figures 12 and 5 report the salaries for the various groups relative to the average salary of a blue collar worker and the within group average respectively. There are three striking observations. First, compositional changes in the workforce are way larger than the changes in relative incomes, which - and this is the second finding - remain relatively stable across hierarchies within group. Third, white collar workers have seen lower income increases than blue collar wokers from 1957 to 1974 and have seen larger increases ever since. The excess growth of white over blue collar workers is 21% for the clerical professions and 13% for technical professions for 1974 to 2003. The hierarchy wage premia remain relatively stable over time, though the lowest hierarchies in the white collar jobs have seen a wage growth pattern that is somewhere between blue and white collar employees. The differential wage

[9]The three main reported groups are: “supervisors” - employees who work independently on tasks that require a high degree of professionality and who typically supervise teams of professionals. They are responsible for the outcome of the work of others. “Professionals” - personnel that works on independently on tasks that require professional experience. Professionals decide independently within their field of responsibility. “Assistants” - personnel that has some professional training and prepares decisions of others but has no decision rights of their own. The data contains a further, lower, white collar hierarchy class, white collar employees that carries out tasks that require no training whatsoever (couriers, porters, etc.). This group is negligible in size.



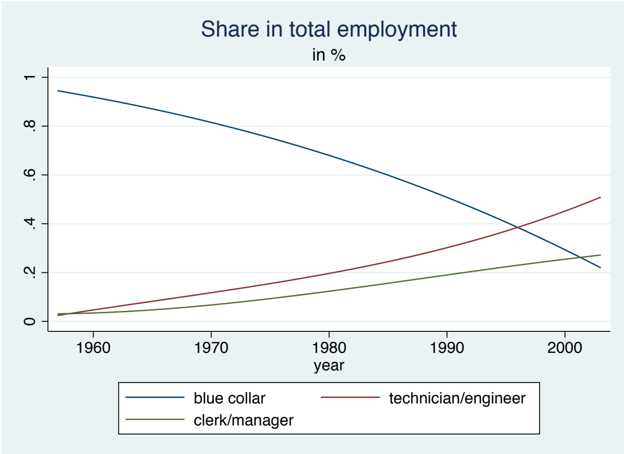
Notes: Hierarchy shares by age in 2006.

growth between white collar workers without discretion on the job relative to those with large discretionary decision power is 10% between 1974 and 2003, see Figure 14 which zooms into Figure 5 by normalizing wage differentials in 1974 to zero. All displayed data is for the production sector.

We use this information to back out the relative importance for the rise of earnings inequality of changes in the composition of the workforce (employment structure) versus changes in relative wage between different groups of workers (wage structure). In other words, we document to what extent it is the increasing share of workers with complex tasks, responsibility, and independent decision making —and hence highest incomes— or the increasing salaries for these tasks that has created the changes in labor income inequality of employees we observe over time.

For this purpose, we extract from our data the share of employees in a cell defined by

Figure 11: Share of Employees by Collar



gender, g, industry, i, and hierarchy h at time t, $s_{g,i,h,t}$ as well as the average wage in the cell $\log(\bar{w}_{g,i,h,t})$. First we calculate the implied cross-sectional variation of wages for every year:

$$\hat{\mu}_t = \sum_{i,h} \log(\bar{w}_{g,i,h,t}) s_{g,i,h,t} \tag{1}$$

$$\hat{\sigma}^2 = \sum_{i,h} \log(\bar{w}_{g,i,h,t})^2 s_{g,i,h,t} - \hat{\mu}_t^2 \tag{2}$$

In addition, we impute the overall income variance in the economy by using the within cell log-income variances from the 2001 micro data, $\bar{\sigma}_{i,h,2001}$.[10]

$$\tilde{\sigma}_t^2 = \sum_{g,i,h} s_{g,i,h,t} [\bar{\sigma}^2_{g,i,h,2001} + (\log(\bar{w}_{g,i,h,t}) - \hat{\mu}_t)^2] \tag{3}$$

Next, we produce alternative series for wage inequality, where we either keep the fractions of workers in cells or their respective wages constant, such that we can decompose changes in income inequality into changes coming from the composition of jobs and changes coming from the wages payed for given jobs.

[TO BE DONE]

[10] In the 2001 micro data, the between cell differences explain roughly 2/3 of the overall income variance and close to 60% of the income variance between male employees in the production sector.

Figure 12: Share of Employees by Hierarchy

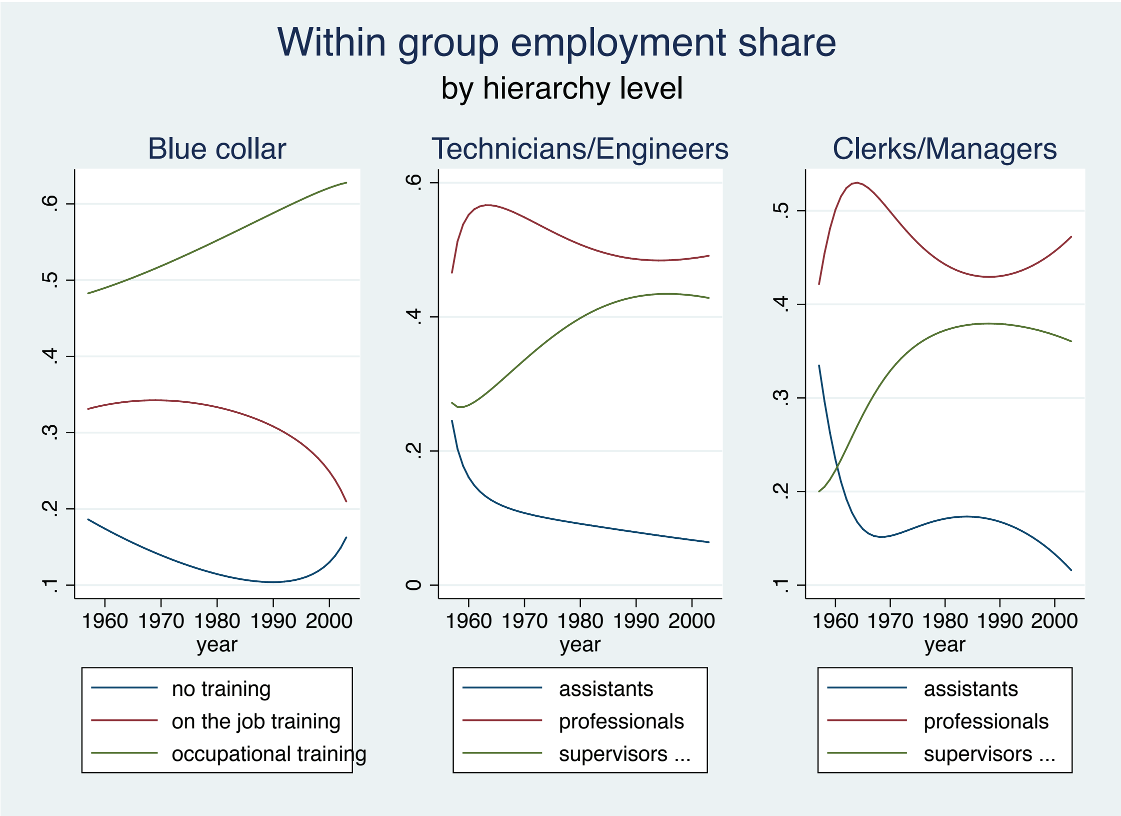
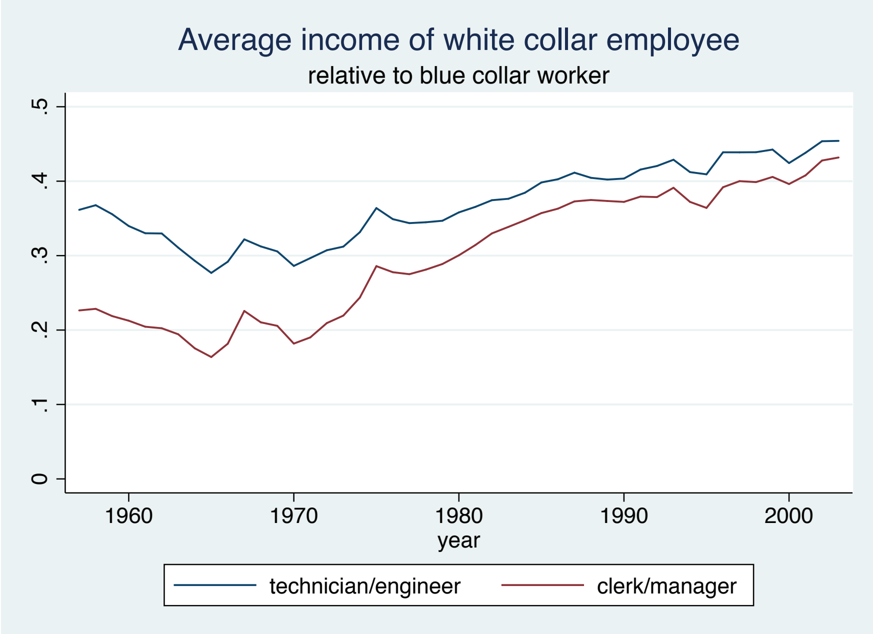


Figure 13: Income by Type of Employment



6 Conclusions

Careers are important to explain wage growth and inequality.

References

Jonathan Heathcote, Fabrizio Perri, and Giovanni L Violante. Unequal we stand: An empirical analysis of economic inequality in the united states, 1967–2006. *Review of Economic dynamics*, 13(1):15–51, 2010.

Jae Song, David J Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. Firming up inequality. Technical report, National Bureau of Economic Research, 2015.

Silvia Strub, Michael Gerfin, and Aline Buetikofer. Vergleichende analyse der löhne von frauen und männern anhand der lohnstrukturerhebungen 1998 bis 2006. Technical report, Schweizer Bundesamt für Statistik, 2008.

Figure 14: Incomes by Hierarchy Levels

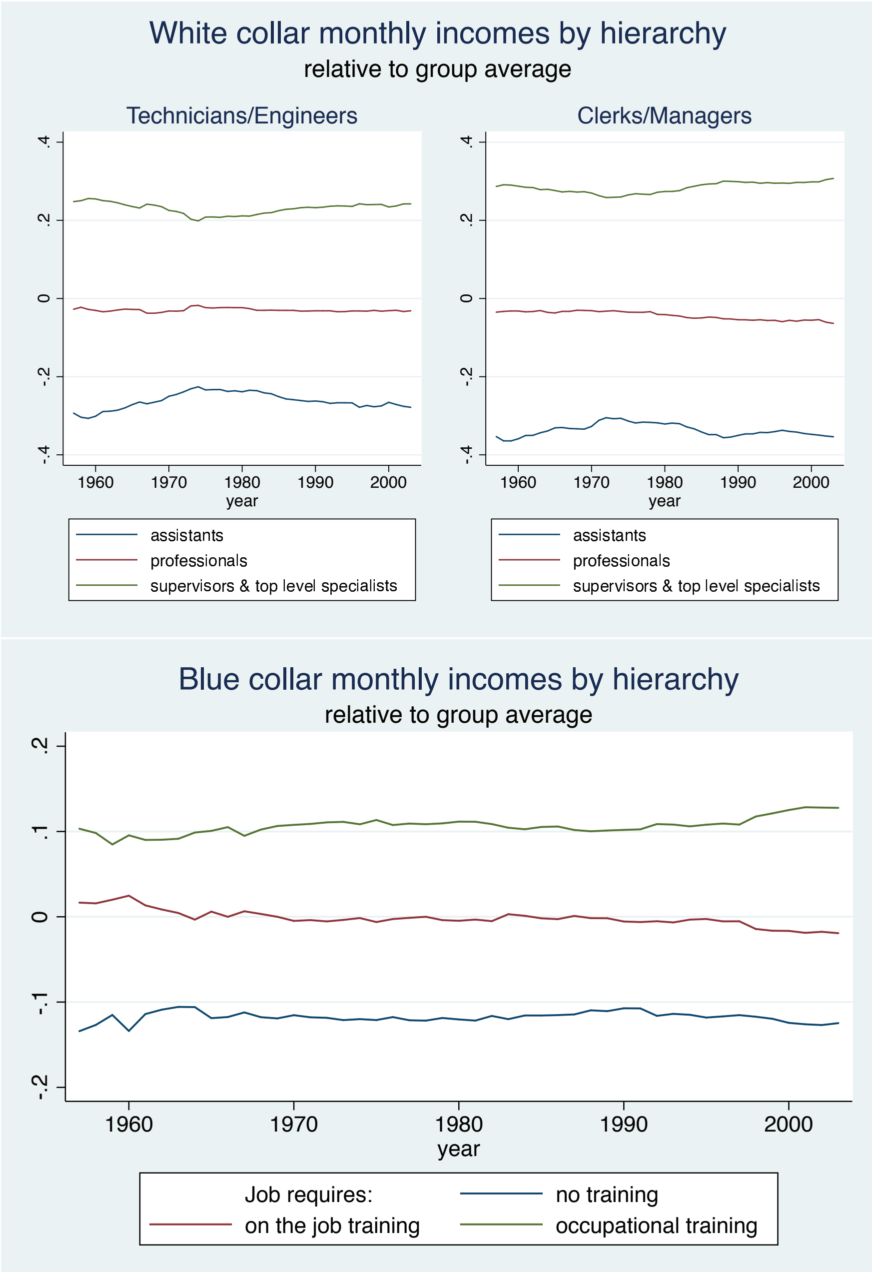
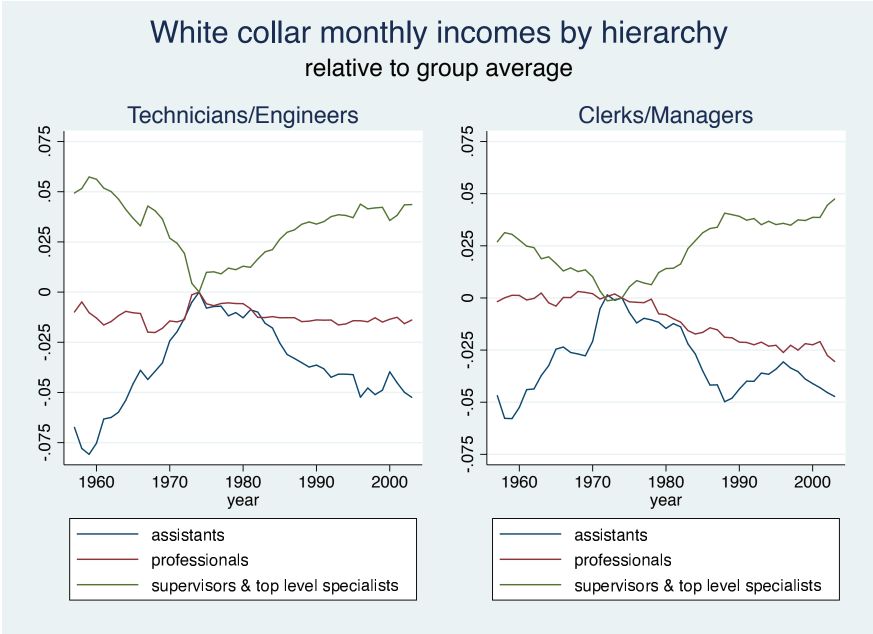


Figure 15: Hierarchical income differences, normalizing 1974 to 0



hierarchy level	share
management	11.7 %
professional	24.4 %
assistant	42.6 %
untrained worker	15.7 %
trained worker	5.6 %

Table 5: Hierarchy shares 2006

A Data details

B Sample censoring

We run the following regression ...